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Assessment of the Impact of a Fully Electrified Postal Fleet for Urban Freight Transportation

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***Abstract* — The progressive electrification of urban distribution fleets, motivated by the consolidation of electric vehicle technology and by the mobility advantages that cities grant to non-polluting vehicles, poses future challenges that affect electrical distribution networks. This paper simulates the main last mile distribution models that can be adopted in a mega-city such as Madrid. In particular, the impact of carrying out the full load of the last mile distribution by means of electric vehicles is analyzed. Two fundamental aspects are studied, the efficiency of the different routes developed by each transport vehicle and the impact that these routes have in the electrical distribution network. For this purpose, an intelligent route planner, capable of optimizing the distribution of the load among the number of vehicles available in each postal service hub (PSH), is combined with a Reference Network Model that designs and expands the distribution network to supply consumers and electric vehicles. Several scenarios in terms of location and segmentation of postal service hubs are analyzed. From this analysis, it is concluded that reinforcements on the distribution network are avoided if the operation is decentralized (using fourteen PSHs), since a centralized operation (a single PSH) would require longer routes with higher energy consumption. Moreover, decentralized operation would enhance de emissions reduction achieved by electrifying the fleet, since the estimated absolute emissions of the electrified fleet for a decentralized scenario are up to 50% lower compared to a centralized one. Finally, the results reveal that smart charging strategies also contribute to lessen the incremental costs in the distribution network, in addition to significantly reducing the cost of energy supply.**

***Index Terms* — Electric vehicle charging, power distribution networks, vehicle routing problem, last mile distribution**

I. Introduction

The prolonged increase in electronic commerce over the last decade has led to profound changes not only in commerce, but also in the logistics and transport sectors [1]. According to a study of the Spanish National Observatory of Telecommunications and the Society of Information (ONTSI) [2], in 2017 more than 31,000 million euros were invoiced in online commerce in Spain, of which 40% will consist of products that require logistics and transport. Limiting these data to the case study analyzed in this paper, in the city of Madrid more than 100,000 parcel shipments are made on average every day [3]. In view of these facts, the need to focus efforts in improving the operation and sustainability of the postal delivery services and, more specifically, the optimization of parcel transport routes, as well as the evaluation of its impact into the system, are needed.

Route planning is one of the most studied fields inside the artificial intelligence and optimization. Problems arisen in this field can be divided into two main groups: the first category of problems are usually known as multi-point routing problems, being the most well-known the vehicle routing problem (VRP) [4] and the traveling salesman problem (TSP) [5]. These problems belong to the field of combinatorial optimization. The second category are the point-to-point route planning problems [6], in which the main objective is to find the shortest path between two different points within a graph.

A common approach to optimize the routing of electric vehicles is an extension of the shortest path problem which seeks to find the most economical route [7]. This may be accomplished by adding constraints to the VRP algorithm that model battery capacity and charging times [8]. In addition to the optimal route, these models also compute the charging time at public charging stations and depot [9]. In [8], the charging price is considered as a constant parameter that depends on time, assigning a different cost to the electricity consumed in each of the 3 periods considered (peak, flat and valley).

Alternatively, an iterative approach to determine the least cost route in interdependent power and transportation networks is proposed by [10]. First, a dynamic route optimization algorithm is used to find the optimal routes and the charging profiles at each spot. Then, a power flow is used to calculate the nodal prices given the expected demand previously obtained from the transportation network optimization. Finally, the electricity prices for each charging station are updated for the next iteration of the routing algorithm.

Although the aforementioned works consider the costs of charging installation and the electricity consumed, they do not provide an analysis of the impact of the electrification of parcels' fleet on electricity distribution networks. Various works have analyzed the challenge of the integration of electric vehicles on small-scale distribution networks [11, 12, 13], but

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they do not focus specifically in the electrification of fleets of freight transportation.

In [14], it is proposed a coupled transportation and power distribution system model, where the transportation model interacts with an Optimal Power Flow in the distribution network, interchanging information about traffic flow and electricity price. In [14], the electricity distribution network is analyzed from the point of view of its operation. In [15], the expansion planning model for distribution systems in the context of plug-in electric vehicles is analyzed. However, that paper that does analyze specifically the delivery of parcels and misses a transportation model. In [16, 17, 18] a joint optimization of distribution networks and electric vehicles is proposed. Moreover, [19] proposes a methodology to jointly optimize multi-energy transportation systems, incorporating transportation, natural gas and active distribution networks. Despite a joint optimization is interesting and could bring benefits for the system, it does not mimic the actual behavior of customers, that first take a decision in their investments and operation, having this kind of decisions later an impact into the system. A different approach that employs a large-scale distribution network planning model to assess the required network reinforcements for different levels of electric vehicle penetration was presented in [20], but not targeting specifically the delivery of parcels, and missing the coupling with a transportation model.

Other authors use generally mathematical models [14, 16, 17, 18], thus limiting the realism and the scale of the distribution systems that can be analyzed. In the state of the art, there are publications analyzing the impact of electric vehicles into the distribution system [11, 12, 13, 14, 15, 16, 17, 18, 19], but there is a lack of such analysis focused in the impact on the electricity distribution network due to the electrification of fleets of freight transportation. Such analysis requires a realistic model of the distribution network around each charging hub. It is also needed to simulate the routes of electric vehicles to model the transportation company and the traffic flows, in order to adequately simulate different options, and estimate the energy requirements of the electric vehicles, since this is a requirement to be able to evaluate their impact into the system.

This paper contributes to the state of the art by proposing a methodology to assess the impact of electric vehicles, by combining for the first time two models, a route optimization model (ROM) and a Reference Network Model (RNM). This approach enables to optimize the routes of the electric vehicles and assess their energy requirements and their impact on the electricity distribution networks. The use of Reference Network Models, allows realistically modeling distribution systems [21, 22], covering all the voltage levels, and enabling to analyze medium or large-scale system, covering all the distribution network around each charging hub. Opposed to other papers that analyze electric vehicles generically, this methodology is applied in this paper, to specifically assess the impact of the electrification of the delivery of parcels, which has nowadays a renewed interest. Moreover, the methodology proposed in this paper mimics (for a proper assessment) the behavior of the agents, considering that transportation companies first take decisions on their investments and operations, which later have an impact in the overall system. Besides, the assessment of the impact in the distribution network, is part of a more complete evaluation that also considers, among others, the reduction of emissions and the cost of energy supply. In term of results, the paper provides real transport routes over estimated workload for last mile delivery in the city of Madrid, allowing to analyze and compare, among others, different strategies for the transportation company (e.g. concentrated vs distributed charging hubs).

Section II presents the transport of parcel context of the problem. In section III, the methodology is presented, describing a decision-making multi-criteria optimization that combines two models to analyze route planning and electricity distribution network modelling. Section IV describes the case study and section V presents the results. Finally, section VI summarizes the main conclusions.

II. Context

Before advancing the methodology for the modelling of both previous depicted stages, it is necessary to delimit the postal delivery services operation and its problematic, more specifically in the so-called Postal Service Hubs (PSH), and what their fundamental characteristics are.

One of the crucial missions of a PSH is the delivery of urgent parcel service and high value-added shipments. To guarantee the fulfillment of the deadlines in the delivery, each unit may have established several work shifts. Each work shift is assigned an PSH boss and a set of postmen. Furthermore, each PSH is assigned a zone of influence, which is given by a series of postal codes, to facilitate the separation of shipments according to their destination and distribution area. In turn, special service units are divided into sections that correspond to a certain geographical area or a group of previously established streets. The sections can be divided into distribution zones, whose number and size are given by the workload and the number of postmen available. A distribution zone usually corresponds to a specific postman.

From the point of view of the optimization of the delivery service that is carried out in the PSH , the main operation can be abstracted in two stages that are carried out in each of the work shifts: assignment and prioritization (A&P) of shipments, for a side, and route layout definition (RLD), by another.

- *Assignment and prioritization of shipments*: this stage of the operation is carried out by the head of the PSH and the objective is double. On the one hand, determine what packages each postman has to deliver; and on the other, estimate if the workload of the postman is greater than the one that can be delivered during his shift, and if so, determine which shipments are discarded to be delivered in the next turn. This process of assignment, prioritization and distribution of cargo requires a deep knowledge of the operation and the areas of distribution of each PSH by their boss. This presents problems for the operation of the services when it must be absent for vacations, medical leave, etc.

- *Route layout definition*: this stage of the operation is performed by the postmen based on their knowledge of the section or area of distribution in which they work and consists in determining the order in which they have to deliver or collect the shipments assigned to them. This process is done manually and requires a good knowledge of the distribution area, so it usually presents many problems when the postmen are inexperienced or do not know their distribution area.

One of the objectives of the system described in this paper is precisely the automation and optimization of these two stages of face, on the one hand, to avoid the problems that are mentioned of dependence on expert knowledge by the head of the PSH and the postmen, and on the other hand, to make the operation more efficient by reducing the time needed for the allocation and packing of shipments, to improve the load balancing between postmen and to reduce the distance travelled by the postmen in their delivery routes (or even reduce the number of routes).

The characteristics of operation and location of PSH is considered in this paper to build the scenarios used to analyze the impact of the electrification of their fleets, considering in a multicriteria optimization: CO_2 emissions reduction, energy supply costs, investments in charging infrastructure and incremental costs of distribution networks along with routing parameters. The following section describes how to optimize this operation from a formal point of view so that the application of optimization methods is possible.

III. Methodology

A. Aggregated decision-making multicriteria optimization

Other authors use combined optimization models, where the decisions of the agents are decided together with the investments in the electricity distribution networks [16, 17, 18]. Opposed to that approach, we use a two-level approach, where first the transportation companies take a decision on their own investments and operation (e.g. number and location of PSHs, number of electric vehicles, route planning,…), and then that decisions have an impact in the system. A conceptual diagram of the proposed methodology to assess the impact of electric vehicles is provided in Fig. 1.

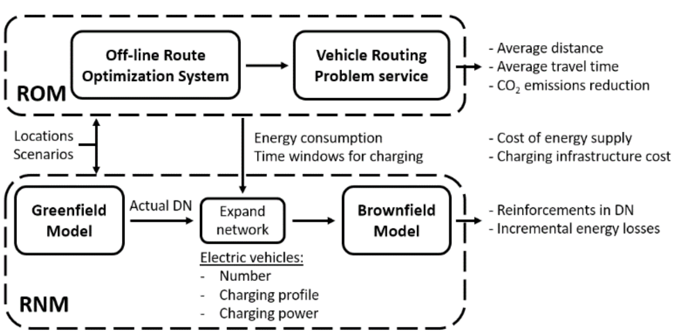

Fig. 1. Conceptual diagram of the proposed methodology

This approach mimics the actual decisions, where Distribution System Operators (DSOs) cannot control their customers' investments and operations. However, as shown in the results section, these decisions later have an impact in the reinforcement level of electricity distribution networks that DSOs must plan and operate. With this solution we provide an accurate calculation of actual investments, where agents first decide upon the investment and operation of their installations, and afterwards the impact of these decisions in the electricity distribution networks is assessed.

In the provided methodology, the daily operation of the parcel delivery company is first modelled using a route optimization model (ROM) taking as an input the position and number of PSHs and the amount of daily shipments per turn of distribution. The average energy consumption per vehicle and time windows in which they are available for charging at the PSH, obtained with the ROM, are then used by a Reference Network Model (RNM) [23]. First, a greenfield RNM (GRNM) is used to obtain a model of the electricity distribution network in the area of interest around each PSH. Then, a brownfield RNM (BRNM) is applied to expand the electricity distribution networks (DN), taking into account the new electric vehicles and their load profile. These profiles also have an impact in the cost of energy and in the required charging infrastructure depending respectively on time and power at which the recharge is performed. The connection between the two models is achieved by using the VRP output data on the energy consumption and the returning time to the depot as input data to the RNM. The data flow between the different components of the framework is better exposed in Fig. 2.

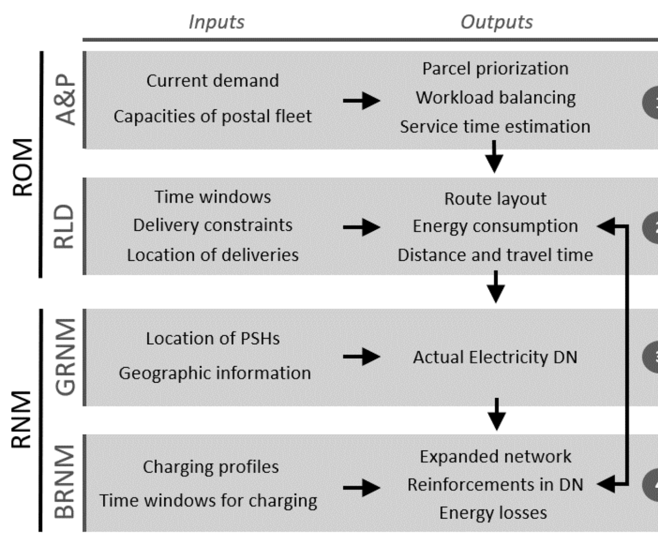

Fig. 2. Data flow of the proposed methodology

A combination of routing, environmental, electrical, and economic parameters is used to analyze scalability and replicability as well as to perform a multicriteria optimization considering the different stakeholders involved. In the case of electrification of fleets of freight transportation, usually freight companies are the ones investing in developing their own charging infrastructure, so not only the energy price but the cost of infrastructure needs to be considered. Moreover, from the point of view of the system, the additional cost of possible network reinforcements required by DSOs should also be studied because they are socialized in the fixed term of the electricity tariff.

B. Route Optimization Model

In addition to the basic versions of the TSP and VRP, in the literature you can find many variants of them. One of these variants is the well-known VRP with windows of time, in which each client imposes a window of time in which it must be visited by the vehicle [24]. Another well-known example is the heterogeneous VRP, in which the vehicle fleet is composed of mobile units of different kinds and, therefore, different cost of use [25]. The optimization of the delivery service stages described in Section II can be modelled using a new variant of the previous methods in which customers can order pickups and deliveries at the same time, with fixed time windows and heterogeneous fleet.

This variant of the VRP is called Vehicle Routing Problem with Simultaneous Pick-up and Delivery or VRP_SPD. Since this problem is a generalization of the classic VRP of collection and delivery, we can model both simultaneous pick-up and deliveries, or well, separate pick-up and delivery. The formulation described here was proposed by A. Tang Mountane et al. [26] and it is given in the next way:

Notation:

V set of clients

V_0 set of clients plus depot (client 0): $V_0 = V \cup \{0\}$

n total number of clients: $n = |V|$

c_{ij} distance between clients i and j

p_j pick-up demand of client j, $j = 1, \ldots, n$

d_j delivery demand of client j, $j = 1, \ldots, n$

Q vehicle capacity

MD maximum distance allowed for any route k

$\tilde{k}$ maximum number of vehicles

Decision variables:

$$x_{ij}^{k} = \begin{cases} 1, \text{if arc}(i,j)\text{belongs to the route operated by vehicle } k \\ 0, \text{otherwise} \end{cases}$$

y_{ij} demand picked-up in clients routed up to node i (including node i) and transported in arc (i, j)

z_{ij} demand to be delivered to clients routed after node i and transported in arc (i, j)

Objective function:

The corresponding mathematical formulation is given by:

$$Minimize \sum_{k=1}^{\tilde{k}} \sum_{i=0}^{n} \sum_{j=0}^{n} c_{ij} x_{ij}^{k} \quad (1)$$

Subject to:

$$\sum_{i=0}^{n} \sum_{k=1}^{\tilde{k}} x_{ij}^{k} = 1, j = 1 \ldots n \quad (2)$$

$$\sum_{i=0}^{n} x_{ij}^{k} - \sum_{i=0}^{n} x_{ji}^{k} = 0, j = 0 \ldots n, k = 0 \ldots \tilde{k} \quad (3)$$

$$\sum_{j=1}^{n} x_{0j}^{k} \leq 1, k = 1 \ldots \tilde{k} \quad (4)$$

$$\sum_{i=0}^{n} \sum_{j=0}^{n} x_{ij}^{\kappa} c_{ij} \leq MD, k = 1 \ldots \tilde{k} \quad (5)$$

$$\sum_{i=0}^{n} y_{ji} - \sum_{i=0}^{n} y_{ij} = p_j, \forall j \neq 0 \quad (6)$$

$$\sum_{i=0}^{n} z_{ji} - \sum_{i=0}^{n} z_{ij} = d_j, \forall j \neq 0 \quad (7)$$

$$y_{ij} + z_{ij} \leq Q \sum_{k=1}^{\tilde{k}} x_{ij}^{k}, \ i,j = 0 \ldots n \quad (8)$$

$$x_{ij}^{k} \in \{0,1\}, \ i,j = 0 \ldots n, k = 0 \ldots \tilde{k} \quad (9)$$

$$y_{ij} \geq 0, \ i,j = 0 \ldots n \quad (10)$$

$$z_{ij} \geq 0, \ i,j = 0 \ldots n \quad (11)$$

The objective function aims to minimize the total distance travelled. (2) ensures that each customer is visited by only one vehicle; and (3) ensures that the same vehicle arrives and leaves each customer it serves. On the other hand, (4) limits the number of vehicles to $\bar{k}$; and (5) sets the maximum distance to cover. (6) and (7) define that the pick-up and delivery demands are met for each customer, respectively.

The purpose of (8) is to ensure that collection and delivery demands are only transported using the arcs included in the solution; furthermore, they impose an upper limit on the total load carried by a vehicle in any section of the route. Finally, constraints (9) - (11) define the nature of the decision variables.

More broadly, the limitations of the problem ensure that each vehicle leaves the depot with a volume equal to the sum of the customer's delivery demands on the route served by that vehicle, that each vehicle returns to the depot with a volume equal to the sum of the customer's collection demands on the same route, and that capacity and maximum distance restrictions are not violated.

To develop this part of the system we used as basis the Vehicle Routing Problem service from ArcGIS on-line[4]. This is a service based on high-performance techniques for vehicle route optimization problems, highly adaptable to different variants and environments. The main reasons that motivated us to base the development of the delivery route optimization system on this service are the necessity for high scalability, fast prototyping and shorter development time, facilitating the testing of different scenarios while focusing on higher level user requirements. Fig. 3. shows a more specific scheme of the proposed route optimization model (ROM), including the VRP service and the modules comprising the off-line route optimization system.

[4] https://developers.arcgis.com/rest/network/api-reference/vehicle-routing-problem-service.htm

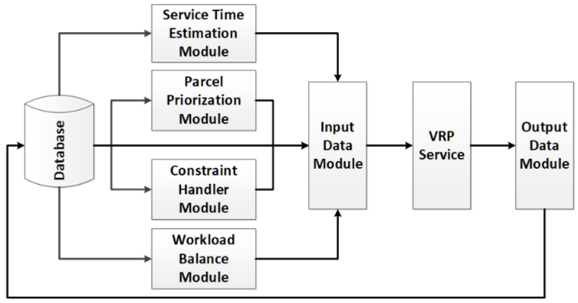

Fig. 3. Functional scheme of the route optimization model.

As can be seen in the diagram, the designed system has several successive functional modules for off-line information collection, analysis and transformation, so that, once it has been modeled according to the characteristics of the problem, it becomes part of the input data for the VRP service. The functionalities of these modules are described below:

The ***workload balance module*** is in charge of calculating some parameters that make the VRP service balance the workload among postmen. In this sense, the workload balance done by the VRP service is based on the volume and location of the current demand with the only purpose of minimizing the total distance travelled while fulfilling the different constraints. However, this form of distributing the workload can also lead to important variances among the workload of the postmen specially in working shifts with a low and geographical concentrated demand. To avoid these inefficiencies in terms of equity among workers, a mechanism to distribute the workload of the postmen more uniformly while increasing as less as possible the total travelled distance has been deployed.

The ***constraint handler module*** calculates the values that set the main constraints of the VRP service. Although some of them have been already depicted with some of the attributes of the input and outputs parameters, we aim at emphasizing and clarifying how these important constraints are modelled. These descriptions are given below:

- *Time window constraints:* established by some especial services (urgent parcels, 24h delivery, etc.) or some contracts with specific clients (mailing for bank offices, etc.) where the parcels must be picked-up or delivered in a specific time frame.

- *PSH opening and closing hour constraints:* the opening and closing hour restrictions that impose the facilities, that in this case it is the PSH. This restriction it is also by the ArgGIS VRP service which allows defining the opening and closing hours of the depot, which corresponds to the PSH in our particular case, through the attributes.

- *Work shift start, end, duration, and workload:* restrictions related to the workforce also play a pivotal role in the operations of the PSH. In this regard, the most important aspects are the starting and ending hours of the working shift, duration of the workday and the maximum workload allowed for a postman.

- *Vehicle capacities:* related to the capacity of the vehicles in terms of weight and volume. In this case, the input parameter involved in the VRP configuration is also *routes* and the attribute is *capacities*, where the maximum weight and volume units are established.

The ***parcel prioritization module*** which computes and estimate the priority of each parcel. There are important clients for which it is very important to maintain certain levels of quality in the compliance of pick-up and delivery times of the shipments (e-commerce, bank offices, clinics, etc.) For this reason, prioritization of parcels is a key issue to model and handle in the postal delivery operation in order to ensure that that those parcels with a sooner delivery deadline and with a high priority are those shipments that are distributed in the current shift in case it is not possible to distribute all available parcels in the current shift. Four priority levels have been deployed with four different values for the *revenue* attribute whose difference was given in various orders of magnitude.

The ***service time estimation module*** that estimates the service time for each parcel according to its geolocation and historical information. The ISMS collects everyday thousands of records about the time at which almost every parcel is collected or delivered by a postman. Taking into account that the address of many of these parcels is also registered, we have available high volumes of information about where and when the shipments are distributed, to which we can add other data as the type of service or parcel, working shift, etc. This information provides great value to estimate the service time. To this end, Fig. 4. show a schema of the different stages that take place along the delivery routes.

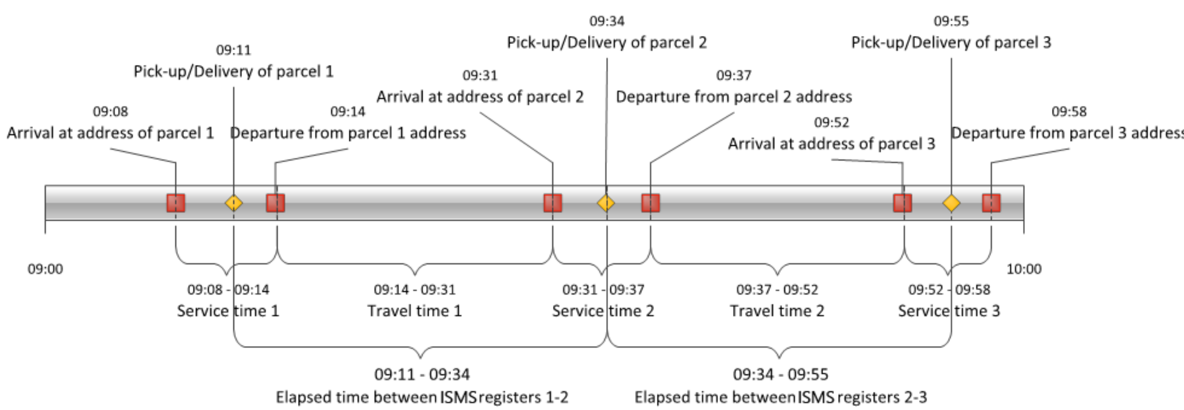

Fig. 4. Schema of different stages and main milestones in delivery routes.

The ***input data module*** gathers and integrate data from the former modules and the database to produce all input data and configuration required by the VRP service to execute. Similarly, the ***output data module*** translates the information provided by the VRP service and stores it in the ***database*** allowing to be used by the reference network models, as described below.

C. Reference Network Models

A large-scale distribution planning model is used to model the distribution grids and assess the impact of the electrification of the delivery of parcels in several scenarios. This model, known as Reference Network Model (RNM), was introduced in [23], [27]. The RNM aims to design the optimal distribution network by combining planning algorithms with a geographic information system (GIS) to minimize the cost of the electricity distribution networks. The objective function comprehends onetime investments along with the present value of maintenance costs and energy losses throughout the lifespan of the network. The RNM's architecture is structured into four layers: i) the logical layer defines the basic structure of the network, such as graphs comprised of nodes and branches, and executes several algorithms, for example to obtain a minimum spanning tree; ii) the topological layer contains, within the GIS, the necessary data and algorithms to optimally locate the geospatial coordinates of the network components following the layout of street maps, which act as a geographic constraint; iii) the electrical layer implements power flow and planning algorithms and defines the electrical attributes of the equipment; and iv) the quality of supply layer, which evaluates and improves system reliability.

The inputs to the RNM are consumers' location and load profile, street maps, a catalog of standardized equipment (feeders, substations, distribution transformers, etc.) and a set of general configuration parameters. Then, the model optimally selects from the catalogue of equipment all the necessary components to supply consumers and connect distributed generation at a minimum cost, while complying with quality and reliability requirements of power supply. This process follows a bottom-up approach, summarized in the flowchart in Fig. 5. starting from the low voltage consumers. First, the supply sources (transformers and substations) are located and sized at every voltage level. For this purpose, we use a minimum spanning tree algorithm that identifies nearby consumers and remove some branches to select which ones can be supplied from the same substation [22]. Then, power lines are planned to supply all loads from these sources while complying with the geographical restrictions posed by street maps, as well as electrical constraints (voltage and thermal limits) and reliability constraints. In order to plan the power lines, we start with an initial configuration. This initial configuration is a minimum spanning tree in the greenfield RNM. This network configuration is the minimum length graph that connects all consumers to the substation but has the problem of not necessarily being technically feasible in terms of congestions and voltage issues. In brownfield RNN, there is already an initial network which is feasible. This model starts analyzing a configuration where all the new consumers are directly connected to the substation. This configuration is verified to be feasible but is usually too expensive. We improve these initial configurations by applying branch-exchange to make them technically feasible (in greenfield RNM), and to reduce their cost (in brownfield RNM) [28].

In addition to a detailed cost record by type of component and voltage level, the results include a complete report of both technical and economic parameters for all designated network components. Moreover, it provides geospatial data of all these network components that has been later used in section IV to create graphical representations of the grids.

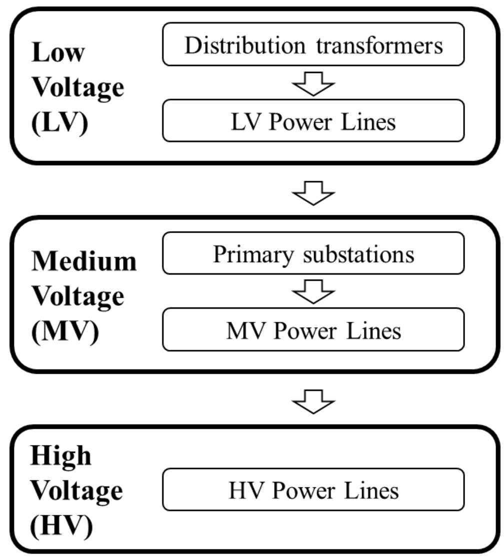

Fig. 5. Reference Network Model flowchart.

First, the actual networks are built from scratch using a greenfield RNM for an area around each of the 14 studied PSHs. These initial networks are then considered in the brownfield RNM as the reference to quantify the costs of the required network reinforcements and incremental energy losses to accommodate the new electric vehicles. This methodology, applied to analyze the impact on distribution grids of different penetration levels of distributed generation [29] and electric vehicles [20], [30], has been adapted to study the future electrification of parcels' fleets, by combining it with a route optimization model.

The greenfield RNM generates from scratch an optimally adapted network to supply the existent loads while meeting technical requirements such as voltage drop, thermal constraints, and reliability. These models minimize DSOs investments and operational costs when connecting network users (consumers, electric vehicles, and distributed generation). The greenfield RNM has already been applied to build European representative networks in [21].These models enable to model large-scale networks, making the analysis and the results more robust and replicable because they are less dependent of particular conditions of an individual feeder.

Once the initial distribution networks have been modelled, they are expanded to analyze the different scenarios by adding the

	Scenario 1 (14 PSH)	Scenario 2 (5 PSH)	Scenario 3a (outskirts)	Scenario 3b (center)
Number of routes	490	500	495	495
Minimum distance	6.043 km	8.201 km	5.625 km	9.206 km
Maximum distance	94.947 km	81.668 km	76.606 km	62.196 km
Total distance	9554.517 km	11216.081 km	19736.054 km	13760.627 km
Average distance	19.499 km	22.432 km	39.871 km	27.799 km
Minimum time	7h 0m 30s	7h 0m 49s	7h 0m 32s	7h 1m 3s
Maximum time	7h 9m 56s	7h 9m 59s	7h 9m 58s	7h 9m 59s
Total time	3484h 53m 0s	3551h 41m 0s	3517h 13m 0s	3518h 52m 0s
Average time	7h 6m 0s	7h 6m 0s	7h 6m 0s	7h 6m 0s
Total consumption	2663.799kWh	3127.043kWh	5502.412kWh	3836.463kWh
Average consumption	5.436kWh	6.25kWh	11.116kWh	7.75kWh
Delivered packages	20355	20630	19635	20035
Unattended packages	5260	5005	5990	5590

Table 1. Generated routes results applying the ROM in each of the proposed scenarios.

new charging spots. A brownfield RNM is used to plan distribution network reinforcements with minimal investments, maintenance and incremental energy losses to accommodate the new electric vehicles. All the newly added electric vehicles are connected to the same charging hub, where the delivery of parcels starts. For every area of interest, several power flows scenarios are analyzed with different number of electric vehicles, charging power and profiles (peak and valley). Finally, the impact on the distribution network is assessed by calculating the expansion network cost in each scenario.

IV. CASE STUDIES

In order to evaluate the real impact of electrification in the parcel delivery processes, we wanted to establish as a general case study an approximation as close as possible to the actual delivery operation that is carried out daily in the city of Madrid. For this, and considering public and statistical data, the position of the PSH and the number of daily shipments per turn of distribution have been established.

These data correspond to a total of 25,000 packages to be delivered per 8-hour shift (1h reserved for loading/unloading and rest), which are normally served from 14 postal service hubs. To do this, nearly 500 delivery vehicles are used (35 on average per PSH) with a maximum load of 50 packages each.

A. Scenarios

In this case study the activity of a major logistic company in Madrid is simulated. Considering the scalability and replicability of the case study, different scenarios have been defined to perform a sensitivity analysis on several parameters:

- Level of dispersion:
    - Scenario 1: decentralized operation with 35 vehicles in each of the 14 PSHs.
    - Scenario 2: semi-decentralized operation considering 5 PSHs, each with 100 vehicles.
    - Scenario 3a: centralized operation of all the 500 vehicles in a single PSH located in a suburban industrial area, corresponding to PSH 2.
    - Scenario 3b: centralized operation of all the 500 vehicles in a single PSH located in a residential area in the city center, corresponding to PSH 1.
- Level of penetration: the addition of 35, 100 and 500 electric vehicles are analyzed for the distribution networks of PSHs 1 and 2.
- Location in industrial or residential areas that have different load curves due to the different ratio between low and medium voltage consumers. Both types of consumers have different load profiles, so the aggregate demand of the existing consumers is different in both cases and the peak is reached at different moments of the day.
- Charging patterns:
    - Peak: starting at 10p.m., when the vehicles arrive at the PSH. This time frame coincides with the evening peak of electricity consumption.
    - Valley: smart charging to fill in the valley (2-6 a.m.).
- Charging power:
    - Slow charging: 3.7 kW
    - Quick charging: 22 kW
    - Fast charging: 50 kW.

In accordance with these scenarios, the input parameters introduced in the route optimization model described in section III.B are shown below:

- *Orders:* the destinations the routes should visit. An order can represent a delivery, a pick-up or a simultaneous pick-up/delivery. The main features of an order are geometry (coordinates), service time, delivery quantities, revenue, and time window (time in which the parcel must be delivered). For the simulation of all the scenarios, which represent the real load of parcels in the city of Madrid for one shift, 25,000 orders have been loaded with different locations, priority values and hard time windows. To do this, a service has been developed generating several random orders based on the actual load by areas of the city of Madrid[5].

- *Depots:* a location that a vehicle departs from at the beginning of its workday and returns to at the end of the workday. Vehicles are loaded (for deliveries) or unloaded (for pickups) at depots at the start of the route. A depot has open and close times, as specified by a hard time-window. Vehicles cannot arrive at a depot outside of this time window. In this case, the depots correspond to the different number and location of PSHs established for each scenario and are also the places where the charging of electric vehicles is carried out.

- *Routes:* routes that are available for the given vehicle routing problem. A route specifies vehicle and driver characteristics; in service response, it also represents the path between depots and orders. In this case, the properties that can be specified are start depot, end depot, start and end service times, max order count and max total time. The properties have been adjusted to the case study, with 50 packages as maximum order count for each vehicle and a maximum total time of 7 hours per route.

B. Generated Routes

Once the parameters and restrictions for each of the scenarios have been established, the VRP service has been launched, and the results have been collected in the database.

Based on this information, and after the analysis of the raw data, the statistical results of each of the scenarios is presented, considering variables such as the total distance or average time per route and average consumption per vehicle (Table I). Screenshots of some of the routes generated and comparisons of the route optimization algorithm with the actual operation of the postmen are also presented.

Considering the results of the ROM shown in Table I, it can be seen that in the number of routes made and the distance traveled, scenario 1 (Fig. 8.), decentralized, with a greater number of PSH and therefore more geographic dispersion, is the more efficient. Similarly, it can be seen how scenario 4 with a single centralized hub is the least efficient in terms of total distance. The difference with scenario 3 is precisely due to the location of that single hub, minimizing the distance in deliveries to companies located on the outskirts of the city.

The data of delivered and unattended parcels follow the same general line, although in this case, the lower number of hubs allows better management, favoring scenario 2 by 5% compared to scenario 1. The values referring to the route time are similar in all the scenarios since they are precisely the limiting factor (together with the number of packages per route and the number of vehicles available) in the optimization of each of the proposed delivery scenarios.

Optimization of delivery via reduction in the number of routes

Fig. 6. and Fig. 7. show, as an example of the optimization achieved, a comparative between the real distribution of parcels done by the postmen (Fig. 6) and the results of the proposed system (Fig. 7) for Scenario 2, PSH2.

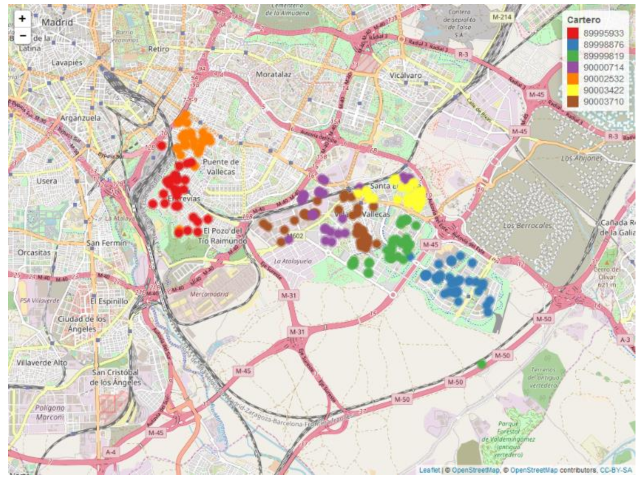

Fig. 6. Distribution of parcels done by real postmen.

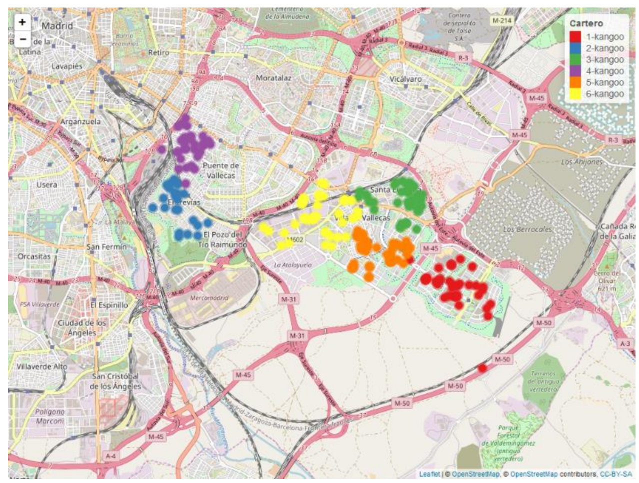

Fig. 7. Distribution provided by the optimization system

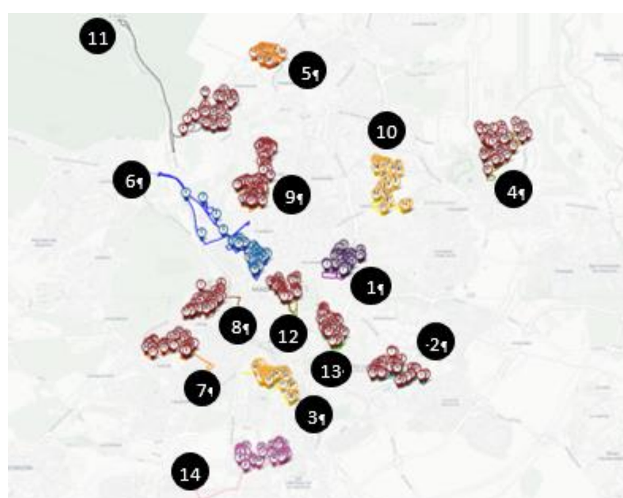

Fig. 8. Location and first route of the 14 PSHs for scenario 1.

[5]http://dev.mobility.deustotech.eu/PostLowCIT/api/EsriSimulacion/Orders?simEnvios=500

PSH	LV cons.	MV cons.	Ratio MV cons.	Transf. centers	HV/MV subst.	LV lines' length [km]	MV lines' length [km]	HV lines' length [km]	I/Imax (element)
1	48383	311	0.64%	206	2	137.70	62.46	6.96	0.86 (MV feeder)
2	60560	532	0.87%	264	2	197.10	89.68	15.64	0.92 (Substation)
3	51536	289	0.56%	217	2	143.31	58.24	10.31	0.98 (HV feeder)
4	48902	558	1.13%	208	2	164.43	85.04	8.75	0.86 (MV feeder)
5	70695	367	0.52%	303	2	206.32	116.17	7.40	0.92 (Substation)
6	47532	260	0.54%	201	2	135.11	52.75	11.17	0.89 (HV line)
7	52017	183	0.35%	218	2	145.79	51.08	10.16	0.93 (HV feeder)
8	47141	327	0.69%	200	2	133.17	48.06	12.48	0.94 (HV feeder)
9	45125	490	1.07%	187	2	145.47	60.24	4.84	0.88 (MV feeder)
10	56560	280	0.49%	241	2	160.54	66.67	6.23	0.85 (MV feeder)
11	5884	44	0.74%	26	1	24.02	7.28	5.86	0.85 (Transf. center)
12	48766	260	0.53%	206	2	138.13	58.49	12.42	0.85 (MV feeder)
13	48766	260	0.53%	206	2	138.13	58.49	12.42	0.85 (MV feeder)
14	58686	587	0.99%	250	2	200.75	95.91	11.00	0.94 (Substation)

Table 2. Generated actual distribution networks results applying the greenfield RNM around each PSH location.

As can be seen, one of the characteristics of the deployed optimizer is that it organizes the routes in such a way that close distance deliveries are carried out by the same vehicle whenever possible. Thanks to this, and compared to the actual execution of the postmen, where some routes are dispersed across the map (different colors/routes in several areas of the map), the number of routes required to serve the same number of packages has been reduced by one (7 to 6 routes).

Fig. 8. shows the distribution and the location of the 14 PSHs arranged in scenario 1. Only the first of the routes, out of an average total of 35 made in each of the PSHs are shown, to facilitate the visualization of its geographical distribution.

C. Distribution network

The PSHs are the starting point for the delivery of parcels and the location where electric vehicles are charged. A model of the distribution networks arround each PSH has been obtained using a greenfield RNM. A summary of their features is presented in Table 2. The areas of interest have been classified according to two parameters. First, industrial (locations 2, 4, 9 and 14) and residential areas are diferentiated for the reason that industrial areas have a greater number of MV consumers. This results in different aggregate demand load profiles. Secondly, distribuition networks in older areas (locations 2, 3, 7 and 8) have been built with less capacity margins for its components. The last column of Table 2 provides a comparison of the capacity margin for the most critical element of the network, whose type is indicated in parenthesis. Finally, PSHs 12 and 13 share the same network since the are located within the same area.

The distribution network obtained for the area corresponding to the first location is illustrated in Fig. 9. as an example. Each voltage level (LV, MV and HV) has been assigned a different color (black, green, and light green). The distribution transformers are depicted as a blue diamond. The width of the lines and the size of the symbols are increased with the voltage level. The HV substations are placed in a real location obtained from the ENTSO-E transmission network map [31].

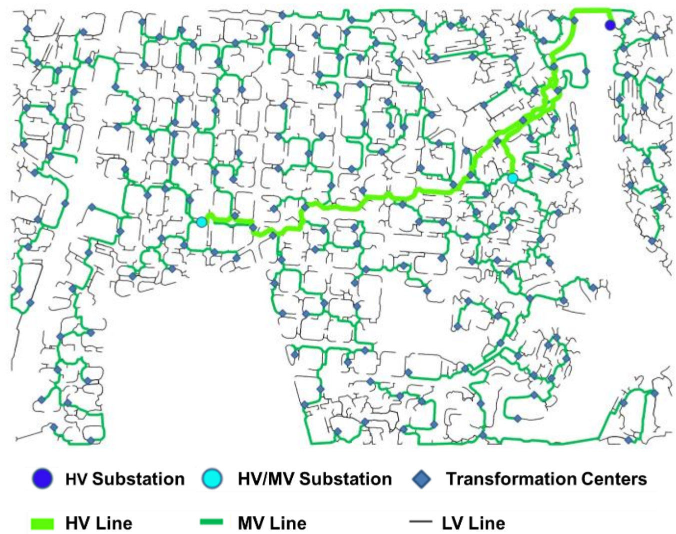

Fig. 9. Base case distribution network for the area of PSH 1.

The cost of energy has been approximated as a constant parameter dependent on the hour of charging. The values assigned for each hour have been obtained from the average for 2019 of the electric vehicle tariff [32], which has two distinct periods valley and peak. The cost of energy supply is obtained by multiplying the power consumed by the tariff for that time. This is not the same as the variable cost of electricity since it includes the socialized costs of the existing network in addition to the price of electricity in the pool. However, it should be noted that this tariff is oriented to small consumers and parcel companies may negotiate bilateral contracts directly with retail companies.

Regarding the electrification cost, an estimate of the capital expenditures of charging infrastructure for the year 2020 in Germany is provided in [33]. The total investment in charging infrastructure increases with power level and consists of four main components: hardware, grid connection, planning and installation. Grid connection costs covered by the consumer, which mainly account for the transformer station, should not be mistaken with the reinforcement costs obtained with the brownfield model that DSOs face to supply the new demand in compliance with the quality of service standards. The study of the later is a relevant contribution this paper and is not part of the charging infrastructure cost. While slow charging at 3.7 kW and quick charging at 22 kW run with AC voltage, DC fast charging at 50kW requires a rectifier increasing hardware cost. Thus, the net costs of a DC fast charging station ascent to 24000€, which is significantly higher than the 1700€ investment required for a 3.7 kW smart box or the 3750€, for a 22 kW charging station. Besides, the charging stations reviewed in [33] are equipped with smart metering, so no supplementary costs are considered to enable intelligent valley filling charging strategies.

The emissions from the electrified fleet for each scenario is estimated taking into account the average of emission factor of the Spanish generation mix (0.17 tCO_2eq/MWh in 2019) [34]. For the previous fleet of vehicles, an emission rate for the diesel vans of 140 gCO_2/km is considered [35].

V. RESULTS

In this section, the results of the case studies presented in section IV are analyzed. First, a sensitivity analysis is performed to quantify the impact of several decision variables on the distribution network. Then, the results are summarized in Table 3 which provides the basis for an aggregated decision-making multicriteria optimization combining routing parameters, environmental impacts, and costs. For the base case scenario, it has been considered that the recharge begins at 10pm (peak hours) and is carried out with and AC 22kW quick charger.

A. Sensitivities

i) Charging profile:

The sensitivity analysis for the charging profile, shown in Fig. 10, indicates that applying smart charging strategies to fill the valley reduces the necessity of reinforcements in the distribution networks. Compared to peak charging, these intelligent strategies reduce the simultaneity factor, especially in fast charging cases. The simultaneity factor is considered here as the probability of vehicles charging at the same time during a specific time window. For instance, the simultaneity factor for peak charging where all vehicles start charging at the same time when they arrive to the depot is 1. Therefore, lower values of the simultaneity factor imply a lesser amount of stress on the grid. In addition, at off-peak hours the components of distribution network have a greater margin over their capacity limits, allowing for more demand to be connected.

In the more decentralized scenarios (scenarios 1 and 2), as there are no investments in reinforcements, the effect of reducing incremental losses may not be sufficient to compensate the additional cost of the smart charging infrastructure. However, when considering a single centralized operations hub, the effect is more noticeable as it eliminates the need of reinforcements to accommodate the 500 electric vehicles. Besides, valley charging provides savings in the electricity bill because the cost of energy supply is much lower during off-peak hours.

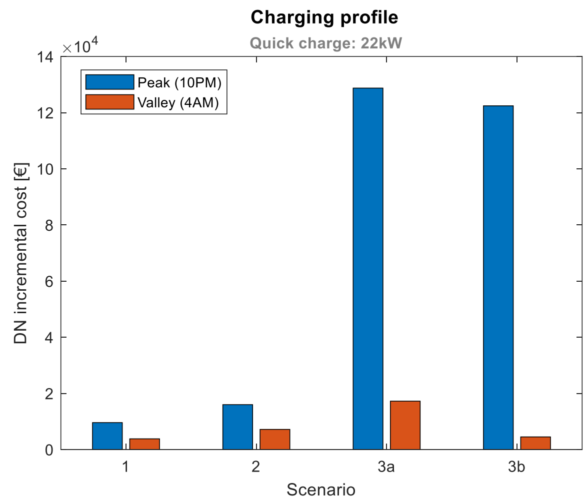

Fig. 10. Dependence of distribution network incremental costs with charging strategies for each scenario.

ii) Number of vehicles:

The number of vehicles is directly related with the increment on demand and therefore, with the necessity of reinforcements in the network. For the base case, there are only reinforcements in the most centralized scenario. Fig. 11 depicts a comparison between locations 1 and 2 as a function of the number of electric vehicles. They follow a similar trend when new electric vehicles are connected to the grid. However, incremental costs in the network at location 2 are slightly higher because it was defined as an industrial area, with a greater number of MV consumers, and has older infrastructure, implying that actual components are closer to its thermal limits.

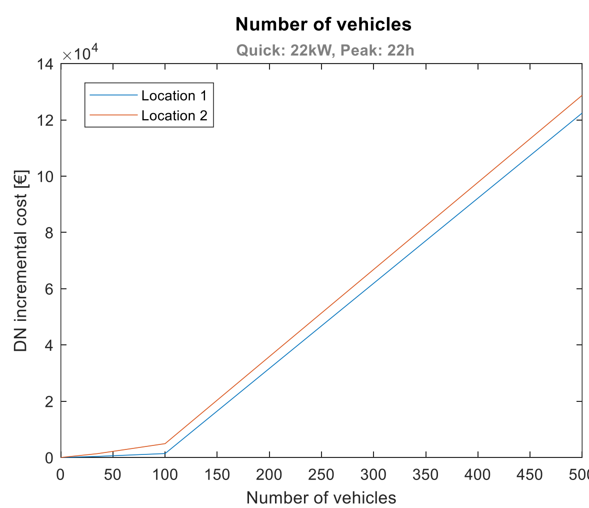

Fig. 11. Dependence of distribution network incremental costs with the number of electric vehicles at locations 1 and 2.

iii) Charging power:

The assessment of the incremental costs of the distribution network with the power of charging (Fig. 12) provides similar results to those of the number of vehicles. This holds for slow and quick charging. However, when comparing the aggregated investments in scenarios 2 and 3a or 3b, the investments in the latter centralized scenarios are lower. This may sound counterintuitive, but when analyzing only one area, the investments increase in steps as the capacity or quality of supply limits are surpassed and an additional element has to be installed. This was analyzed previously in Fig. 11. Therefore, the individual percentual increments in each of the 5 areas in scenario 2 are lower, but their aggregated cost is greater.

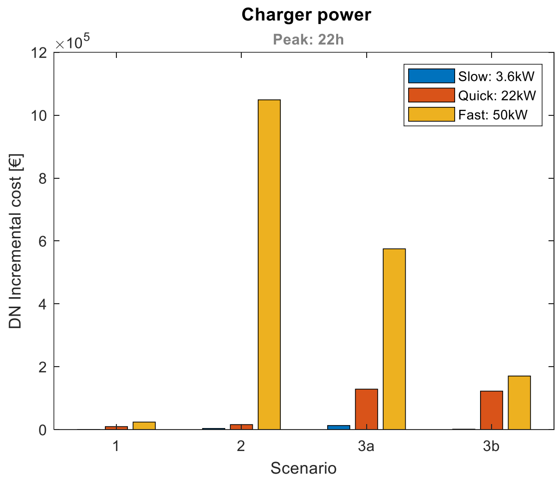

Fig. 12. Dependence of distribution network incremental costs with charging power level for each scenario.

Moreover, the costs in scenario 3a, where the PSH is located in an older industrial neighborhood in the outskirts, are higher than in the other centralized scenario 3b. As mentioned earlier, the initial MV network in scenario 3a is more congested, but the difference between both increases with a higher power level. Furthermore, the electrification cost also raises when the power level increases. The installation cost for AC charging infrastructure, both slow and quick charging, is lower than DC fast charging.

B. Multi criteria optimization:

The results from the simulations for all the scenarios carried out with the methodology explained in section III are summarized in Table 3, which provides the foundations for a multi-criteria optimization for the different stakeholders involved in the aggregated decision-making process in which transportation and electrical network parameters are closely related.

The greater dispersion of the depots decreases the average distance covered daily by each vehicle. This reduces the energy consumption and, as a result, the cost of energy supply. Moreover, the results in Table 3 reveal that required reinforcements on the distribution network to accommodate the new electric vehicles could be avoided if the operation is decentralized (Scenario 1). Furthermore, the relative CO2 emissions reduction achieved by substituting the current fleet with electric vehicles (66.15%) could be enhanced by decentralized operation because it results in shorter delivery routes. For instance, as shown in Table 3, the estimated absolute emissions from electric vehicles for Scenario 1 (decentralized)

			Routing parameters		***Environmental***	***Costs***			
Power	**Profile**	**Scenario**	**Average Distance [km]**	**Average Energy Consumed [kWh]**	**Emissions from EVs [gCO$_2$]**	**Energy supply [€/day]**	**Charging infrastructure [€]**	**Reinforcements in DN [€]**	**Inc. energy losses [€]**
3.7 kW (*Slow*)	**Peak**	**1**	19.50	5.436	924	300.43	850000	0	3342
		2	22.43	6.254	1063	327.58	850000	0	3777
		3a	39.87	11.116	1890	488.54	850000	0	13076
		3b	27.80	7.750	1318	377.40	850000	0	3330
	Valley	**1**	19.50	5.436	924	144.46	850000	0	1483
		2	22.43	6.254	1063	166.20	850000	0	2019
		3a	39.87	11.116	1890	205.96	850000	0	8250
		3b	27.80	7.750	1318	295.41	850000	0	1660
22 kW (*Quick*)	**Peak**	**1**	19.50	5.436	924	361.63	1875000	0	9599
		2	22.43	6.254	1063	416.05	1875000	0	15996
		3a	39.87	11.116	1890	739.49	1875000	121624	7117
		3b	27.80	7.750	1318	515.57	1875000	118821	3610
	Valley	**1**	19.50	5.436	924	144.46	1875000	0	3826
		2	22.43	6.254	1063	166.20	1875000	0	7181
		3a	39.87	11.116	1890	205.96	1875000	0	17244
		3b	27.80	7.750	1318	295.41	1875000	0	4511
50 kW (*DC Fast*)	**Peak**	**1**	19.50	5.436	924	361.63	12000000	0	24045
		2	22.43	6.254	1063	416.05	12000000	1045001	31281
		3a	39.87	11.116	1890	739.49	12000000	583603	-8669[6]
		3b	27.80	7.750	1318	515.57	12000000	168248	2320
	Valley	**1**	19.50	5.436	924	144.46	12000000	0	10967
		2	22.43	6.254	1063	166.20	12000000	0	18544
		3a	39.87	11.116	1890	205.96	12000000	115878	25417
		3b	27.80	7.750	1318	295.41	12000000	117593	20852

Table 3. Results of the case study (base case highlighted in grey).

[6] This column shows the increase in energy losses for each scenario respect the base case with no electric vehicles. The negative value in this cell indicates that energy losses in this particular scenario are lower than in the base case. Typically, higher load in the system would increase energy losses, but network reinforcements can push in the opposite direction, reducing impedances and thus energy losses. In this particular scenario, the decrease due to the reinforcements is higher than the increase derived from the load increase.

are 51% lower than in Scenario 3a (centralized). Nevertheless, electrifying longer routes from a current fleet would increase the savings on fuel costs, given that electricity supply costs are lower than fuel costs.

On the other hand, the addition of a higher number of vehicles connected to the same node requires greater investments in the distribution network for that particular area as shown in Fig. 11. However, when considering the total cost of the different areas of interest, they may be higher since the costs increase in steps. For instance, it was previously discussed that the additional costs for DC fast charging in the centralized Scenarios 3a and 3b are lower than in Scenario 2. In addition, a greater charging capacity also increases charging infrastructure costs, especially in the case of DC fast charging.

Finally, the charging profile is the key driver of the cost of energy supply, as the tariff has two distinct regulatory periods, being cheaper to recharge during off-peak hours. Therefore, smart charging strategies to fill in the valley result in lower electrical energy costs. Furthermore, since capacity margins of the existing components are higher during valley hours, both incremental costs in energy losses and reinforcements in the distribution network are also reduced.

VI. Conclusions

This paper proposes a methodology that combines routing optimization and large-scale distribution planning algorithms, to perform a realistic assessment of the electrification of parcels' transportation following the actual decision patterns of the stakeholders.

The obtained results reflect that, for the considered activity level of a parcel delivery company in the city of Madrid, a more distributed layout is better from both a routing and electrical perspective. The impact on the grid is minimal since, with a distributed layout, no reinforcements would be required to supply the newly added electric vehicles. In addition, delivery vans would cover the shortest routes as the PSH is closer to the delivery locations. Therefore, by lowering the average energy consumption both investments in electric vehicles (fewer capacity requirements for the batteries) and the energy supply cost for the parcel delivery company would be reduced. Even in centralized scenarios, current battery technology provides sufficient capacity for daily operation. Moreover, from an environmental point of view the relative emissions reduction from electrifying the fleet would be complemented with lower absolute CO_2 emissions in decentralized operation since vehicles cover shorter routes. On the other hand, centralized operation could result in lower logistics and land expenses, not considered in this paper. In addition, higher savings in fuel costs from electrifying longer routes could ease the investments in electrification.

The analysis of charging strategies shows that, when the charging station is capable of smart charging, it is always better to charge during valley hours because energy supply costs are lower. In addition, besides increments in energy losses (which are also lower when compared to peak charging), there are no additional costs for the DSO since no network reinforcements are needed for AC charging in valley. Thus, price signals or other incentives could be used to encourage smart valley charging in order to reduce congestion in the grid.

Regarding the power of charging stations, 3.7 kW slow charging requires the lowest investments in charging infrastructure. Since no delivery takes place during the night, vehicles stay for a long period at the PSH and low charging times are not critical. Therefore, DC fast charging seems to be better suited for charging stations in transit due to is high infrastructure cost. However, 22 kW quick charging could provide a more flexible alternative for a future increment of the capacity of the vehicles (to cover longer routes, extending the operating hours).

In the analyzed case studies, the most relevant component of the reinforcements in the distribution networks were the additional MV feeders required to supply the new loads when the capacity of the existing ones was surpassed. The hosting capacity for the modelled grids appears to be between 5 and 11MW or 11 and 25MW for peak and valley charging respectively, but a more detailed specific analysis could be carried out in future studies. Finally, further integration between the ROM and RNM could be developed in future research, specially, creating a feedback loop to adapt the scenarios and locations of PSHs with the routing and electrical results obtained.

VII. Data Availability

Datasets related to this article can be found in [35, 36] and are linked to this paper. [36] contains the orders (pickup and delivery locations for postal services) in JSON format, inputted to the route optimization model. [37] contains the synthetic distribution networks in MATPOWER format, which have been used in this paper to model the distribution networks around each PSH, and analyzed with the Brownfield Reference Network Model to estimate the required reinforcements in the distribution system.

VIII. Acknowledgements

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